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Knowledge Base, Information Search and Intention to Adopt Innovation

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Innovation is a process that involves searching for new information. This paper builds upon theoretical insights on individual and organizational learning and proposes a knowledge based model of how actors search for information when confronted with innovation. The model takes into account different search channels, both local and non local, and relates their use to the knowledge base of actors. The paper also provides an empirical validation of our model based on a study on the search channels used by a sample of Dutch consumers when buying new consumer electronic products.

Key words: innovation; knowledge base; search; consumer learning

1. Introduction

Innovation is a process that involves a search for new information. According to March (1991), firms have to balance their search effort for new knowledge (exploration), with the exploitation of existing knowledge. This search for new information prior to innovating is not only limited to the behavior of organizations, but also characterizes the behavior of other types of actors confronted with innovation, such as consumers. In this paper we will focus on the exploration phase of innovation. Our first aim is to contribute to a theory that explains the relation between an actor's knowledge base, the use of different channels for information search and the intention to buy or adopt an innovation. This will be done by combining consumer behavior arguments (e.g Rogers, 2003; Ajzen, 2005; Ratchford, 1982; Johnson and Russo, 1984, Beatty and Smith , 1985; Srinivasan and Ratchford, 1991; Gregan-Paxton, 1997; Yeh and Basralou, 2006) with concepts used to explain innovative behavior (e.g. Nelson and Winter 1982, Aversi et al, 1999, Devetag, 1999; Cohen and Levinthal (1990).

We rely upon three important behavioral assumptions to build our model.

The first underlying behavioral assumption that we will make is that actors are characterized by bounded rationality (Simon, 1955, 1978) so that they are constrained in terms of cognitive and computational resources that they can exploit to absorb information, solve problems and take decisions. This behavioral assumption bears indeed validity both at the individual and at the organizational level. It also justifies our focus on the role of an actor's knowledge base as reflecting their cognitive and information resources. Under bounded rationality learning becomes the crucial process for understanding decision making and behavior formation.

Second, following the evolutionary economics view, actors use search to gather information aimed at either innovation or imitation (Nelson and Winter, 1982). Search is assumed to work as a mechanism spurring change and learning, characterized both by a high level of uncertainty and by a contingent nature.

Third, actors are embedded in social networks and their behavior relies on a combination of social and individual learning, rather than being the result of an isolated rational decision making process (see for instance Aversi et al 1999 for consumers and Greve (1998) and Levitt and March, 1988, for organizations).

The second aim of this work is to provide an empirical validation of our theoretical model based on a study in which we analyze the empirical relationships between the ownership of consumer electronic products among Dutch consumers and their use of different communication channels. A recent contribution that relates closely to our own study comes from Borgatti and Cross (2003). They propose that information seeking is a function of “(1) the extent to which a person knows and values the expertise of another, (2) the accessibility of this person and (3) the potential costs incurred in seeking information from this person.” Their empirical findings indicate that search costs are not significant for the choice of the source of information. However, in developing our theory we will use search costs as the prime unobserved explanatory mechanism for information search channels. Borgatti and Cross (2003) do provide several possible explanations as to why search costs were not significant, which ultimately justify the use of search costs as an explanatory factor. Our empirical results can help advertisers and marketers of innovative consumer electronics to further develop effective communication strategies through the various channels in relation to the consumers existing knowledge base. In addition, managers may use our results to improve their marketing strategy, by gaining more insights on the search behavior of consumers.

In the next section we will develop a theoretical framework for the relationship among the knowledge base, the types of information search and the intention to adopt innovation. Afterwards we present our research methods, followed by the results and a discussion. In the conclusions, we discuss further applications of our model to different domains and different actors.

2. Theory

While we use consumers and consumer electronics as a test case in this paper, our aim is to develop a theory that is more broadly applicable. This theoretical exercise leads us to integrate theories that are formulated on the individual level with theories developed for organizational behavior. Combining theories from multiple levels provides us with the opportunity to develop a quite general model that explains the use of channels for information search. At the same time this exercise requires some caution, because although the effects found at both levels, the driving mechanisms behind the effects could be completely different. Among all the theories from which we draw inspiration, the knowledge based view may be easily applied both at the individual and organizational level. In fact, Cohen and Levinthal (1990), build their understanding of organizational learning processes starting from insights found at the individual level.

They stress the conceptual issues involved in moving from an individual to an organizational level, but they ultimately demonstrate the validity of their knowledge based framework at both levels.

The ideas from evolutionary economics are quite general and can also be applied easily to individual level, as has been done previously by Bettman et al. (1998), Aversi et al. (1999) and Devetag (1999).

2.1 Knowledge base and learning

According to the definition in Rogers (2003), an innovation is "an idea, practice or object that is perceived as new by an individual or other unit of adoption" (p.12). The innovation can be viewed as stand-alone or as being part of a perceived larger whole, for example a technology cluster (LaRose and Hoag, 1996, Rogers, 2003; Vishwanath and Chen, 2006) or a product domain (Goldsmith et al, 1995; Van Rijnsoever and Donders, 2007). The ownership of parts of this larger whole can be viewed as an indicator for the knowledge that an actor has of the total larger whole. In this paper we will focus on the level of the product domain, although our theory may also be applicable on other levels of perception. Our dependent variable is the intention to adopt new innovations within a given domain.

We will begin to build our theory from the knowledge based arguments used by Cohen and Levinthal (1990). They claim that agents absorb new knowledge using their existing knowledge base; the knowledge and experiences they have gathered in the past. A limited knowledge base implies bounded rational decision making. Agents do not have the information, or the mental capacities to make fully rational choices (Simon, 1955; March, 1978). This certainly applies to decisions that are loaded with high amounts of uncertainties such as the decision of whether of not to innovate (Nelson and Winter, 1982). In the first place, we define the size of the knowledge base as the number of innovations already adopted by an actor.

To enhance the existing knowledge base new information has to be searched and learning has to take place. Evolutionary economics has used similar arguments to explain behavioral search patterns. Following Cyert and March (1963), Nelson and Winter (1982) assume both a "local" search, to incrementally improve existing techniques, and an imitation mechanism, by which an organization can adopt behavioral patterns from competitors (Lewin et al, 2004).

Depending on its newness, adopting a first innovation in a domain is a step that involves a relative large amount of risk (Hoeffler, 2003; Rogers, 2003). The knowledge base is formed after the adoption of this first innovation. According to Bandura (1977) and Greve (1998), for the next decision to innovate the actor can:

- Use individual learning and assess the potential in view of previous experiences (Gregan-Paxton and Roedder John, 1997; Yeh and Barsalou, 2006). This is called internal search in consumer behavior theory (Blackwell et al, 2001)
- Use social learning and asses the potential in view of current experiences of others (if available) (Blackwell, 2001; Rogers, 2003; Richerson and Boyd, 2005). This is called external search in consumer behavior theory (Blackwell et al, 2001)

In general the latter is more efficient than the former, because one can choose only to adopt successful behavior (Boyd and Richerson, 1985; Richerson and Boyd, 2005). Once the new behavior has been adopted and proven successful, the behavior is more likely to be repeated (Homans, 1974; Bandura, 1977; Gavetti and Levinthal, 2000). A process of incremental improvement takes place, allowing the behavior to be developed further into a skill or routine. In consumer research, it has indeed been shown that prior knowledge leads to more routinization in learning about new products (Wood and Lynch Jr., 2002). Since the following innovations all fall within an existing knowledge base, they entail less uncertainty and are more easily adopted. In this way, they represent incremental innovations within an existing technological trajectory (Dosi 1982, Gatignon et al., 2002).

A knowledge base is therefore both a means to enable more rational decision making and an incentive mechanism for further learning. Since we consider innovations within a given knowledge domain, we can characterize the knowledge base simply by its size. In the next section, we will relate the size of the knowledge base to various forms of learning and to the intention to adopt new innovations; for each relationship an hypothesis will be formulated. Our conceptual model is depicted in Figure 1.

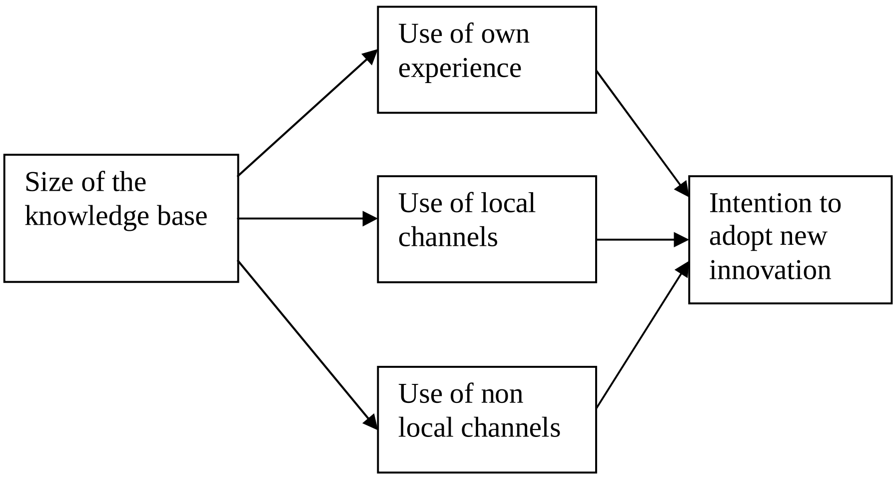

Figure 1: The proposed relationship among the knowledge base, the channels of information search and the intention to adopt new innovations.

2.2 Knowledge base and channels for information search

The size of the knowledge base can influence the type of learning used in the search for new innovations. As we stated previously, actors can learn through their own experience or through communication channels. In this paper, we distinguish two types of search channels, local[1] and non-local. Local search channels are the relations an actor has with the people with whom he or she has direct interaction in his or her social environment (e.g. friends and family); non-local search channels are the information sources that do not require a direct local-interaction from the actor (e.g. watching TV, listening to the radio or surfing the internet). In our case, this distinction runs parallel to the distinction between personal influence and mass media (Katz and Lazarsfeld, 1964), but their distinction is not applicable to other types of actors, hence we will use the broader definition. The choice of an information source to evaluate an innovation depends on the minimization of the amount of effort (or search costs) one has to make to gather the re-

[1] The term local search does not apply here as used by Nelson and Winter (1982) and Rosenkopf and Almeida (2003). They state that a local search is a search that is close to actors existing competences. In our view all searches are also directly related to the knowledge base, but that does not imply anything about the information search channels used. Our term local search is defined in terms of direct contact.

quired information (Ratchford, 1982, Moorthy et al, 1997). Many factors help to determine search costs. According to Borgatti and Cross (2003) search costs can consist of loss of reputation by admitting ignorance, obligations resulting from knowledge exchange and physical distance. Examples of other types of costs could be additional forms of distance (such as cognitive, geographical, organizational, social or institutional; see Boschma, 2005), the amount of time invested, or the actual monetary costs; this depends on the actual context of the actor. We assume that the amount of effort is lowest if actors use only their own experience, then a local search requires least effort. The non-local search requires most effort.

Actors with a small knowledge base are not as able to assess new innovations with the use of their own experience (Rogers, 2003). The ability to rely on the use of personal experience is thus expected to increase with the size of the knowledge base.

H1: The larger their knowledge base, the more likely that actors use their own experience to learn about innovation.

Actors with a limited knowledge base cannot rely on their own experience, they can however get ideas or assess the potential of a new innovation by observing their peers or communicating with them (Richerson and Boyd, 2005). This means that actors can learn socially from individuals that have already adopted the innovation. Since the local search channels provide all the information that is required, there is little need to put any effort in non-local channels.

Actors that have adopted a more than average amount of innovations also have a knowledge base that is larger than average. After a certain critical point, extending that knowledge base through local search channels becomes ineffective, because the actors knowledge base is larger than the knowledge base of their peers. The use of these channels will therefore decline and we predict an inverted U-shape relationship:

H2: The relationship between the size of the knowledge base and the likelihood of using information from local search has the form of an inverted U-shape.

Once actors have explored most information available from local channels, they turn to information gathered from non-local channels. After a certain point, non-local search is likely to become either uninformative or too costly. Actors then rely solely on their own prior experience.

H3: The relationship between size of the knowledge base of an actor and the likelihood of using information from non local search has the form of an inverted U-shape.

The predicted relationships are shown in Figure 2. Note that we expect the peak of the relationship of H3 to be at a higher knowledge base than the peak predicted by H2.

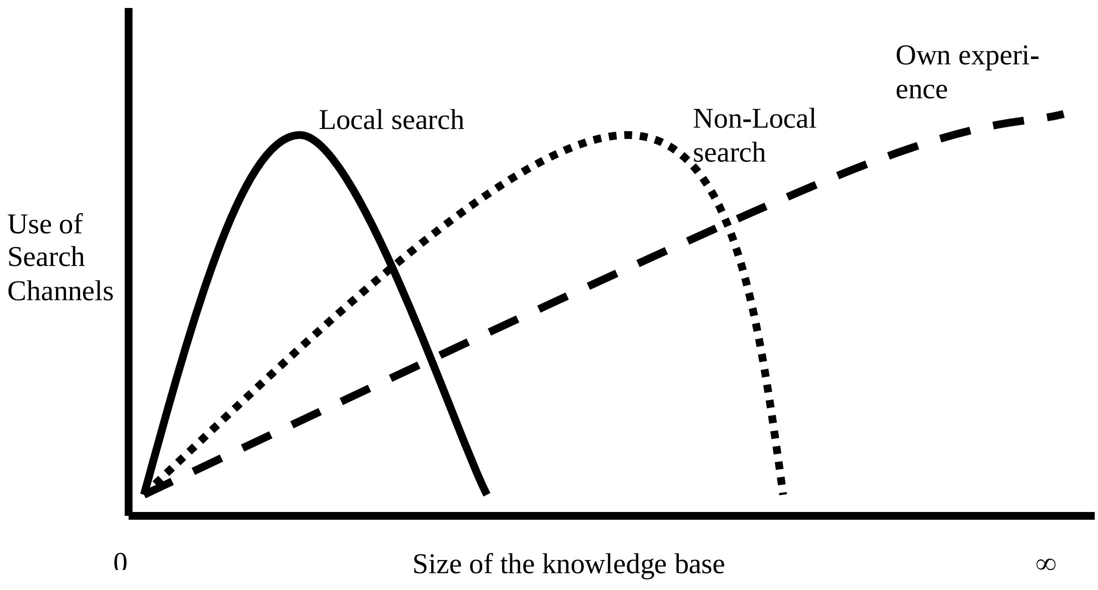

Figure 2: A graphical display of the relationships between the size of the knowledge base and the use of channels for information search.

These relationships resemble theoretical models used by Johnson and Russo (1984) and Moorthy et al (1997), who also claim that the knowledge base is related in an inverted U-shape to external search. External search is there defined as: "*The degree of attention, perception and effort directed toward obtaining environmental data or information related to the specific purchase under consideration*" (Beatty and Smith, 1985). The difference here is that we relate the inverted U-shapes specifically to social learning processes and various search channels, while the linear relationship is related to individual learning. Therefore, our model can be viewed as an extension of the model by Johnson and Russo (1984), where we distinguish between different search channels. Furthermore, our arguments are based on economic arguments related to search efforts, rather than on cognitive abilities. Moorthy et al (1997), also use economic arguments to explain the inverted U-shape, however their arguments do not involve a comparison between the knowledge base of various actors, an element that is crucial for any explanation involving social learning.

2.3 Knowledge base, search channels and the intention to adopt new innovations

Does the size of the knowledge base influence an actor's aspiration to adopt even more new innovations? Following the knowledge based argument discussed above, a broader knowledge base reduces uncertainty about an innovation, increasing the likelihood of adoption.

To answer the question in more detail we will turn to the theory of planned behavior by Ajzen (2005). This theory states that behavioral intentions are influenced by the attitude towards the behavior, a subjective norm (the perception of how the behavior is valued by others), and the perceived behavioral control. In our application of the theory the knowledge base directly influences attitude towards the behavior and the perceived behavioral control.

The argument for the effect on attitude goes as follows: as you adopt certain innovations that are conditional for being able to use other innovations, you are also better able to asses how these other innovations might be advantageous for you. If you own for example a computer with a broadband internet connection, then you are better able to asses the potential value of a webcam, compared to a situation where you do not own those first products (Gregor Paxton and Roeder John, 1997; Yeh and Basralou, 2006). If the previous experiences with those innovations are positive, it is expected that the actor will develop a positive attitude towards the next innovation. This positive attitude will increase the intention to adopt the new innovation (Ajzen, 2005).

A greater knowledge base will also increase the perceived behavioral control. Adopting an innovation is per definition a bounded rational decision process, because innovation is always connected to uncertainty (Greve, 1998, Rogers, 2003; Becker, 2004). Having more knowledge and experience, however, can reduce this uncertainty dramatically, which in turn will increase the perceived behavioral control and therefore the intention to adopt a new innovation.

There is however a limit to the amount of different innovations one can adopt in the same domain at a given point in time, and therefore there is also a limit to the amount of innovations one can aspire to adopt. Since the knowledge base is related to the actual previous adoption of innovations, we expect a saturation effect which translates into an inverted U-shaped relationship:

H4: The relationship between the size of the knowledge base and the intention to adopt new innovations has the form of an inverted U-shape.

Our arguments about the role of the size of the knowledge base in shaping intention rely on the importance of actors accumulating experience. We then also expect a direct effect of the use of one's own experience on the intention to adopt new innovations:

H5. The use of one's own experience to learn about innovation is positively related to the intention to adopt new innovations.

The third mechanism shaping behavioral intentions points to the formation of a subjective norm that informs actors that their intentions are legitimate. We assume that the subjective norm is influenced by local and non-local communication channels. If the information from these channels is favorable, the subjective norm will change positively and the intention to adopt a new innovation will increase.

H6. The use of local communication channels to assess new technologies is positively related to the intention to adopt new innovations.
H7. The use of non-local communication channels to assess new technologies is positively related to the intention to adopt new innovations.

We also wish to relate all the concepts in our model and we propose, following the previous hypotheses, that the effect of the size of the knowledge base on the intention to adopt innovations is mediated by the use of the different information channels:

H8. The relationship between the size of the knowledge base and the intention to adopt new innovations is mediated by the actor's own experience and the use of local and non-local information channels.

In the next section we empirically validate our model and test the formulated hypotheses for the decision to purchase consumer electronic products in a sample of Dutch consumers.

3. Data and Methods

For the purposes of this study, a survey was administered to a sample of Dutch consumers. Quota by age groups and sex were used to ensure a representative sample. This resulted in a sample of 2094 consumers, varying in age between 16 and 88 years (mean = 44.3); 1046 respondents were male, 1048 were female. The written questionnaire enquired, among other things, whether the consumers owned one of 15 following technologies or wanted to own it. The technologies were:

1. PDA
2. HDTV

3. iPod
4. Flatpanel television
5. Game console
6. Webcam
7. MP3-player
8. Notebook or laptop
9. Dolby-surround system
10. Mobile telephone with camera function
11. Digital camera
12. Broadband internet
13. Desktop
14. DVD-player
15. Mobile Phone

We realize that some of these products have overlapping functionalities. A game console for example might also function as a DVD player. These overlapping functionalities were controlled as much as possible during the data collection by asking specific questions that excluded the potential overlap.

All questions were asked in the form:

I own a (*one of the 15 products*) O – No, and I do not intend to purchase this product

O – No, but I do intend to purchase this product for sure

O – Yes, this is the first time I own this product

O – Yes, this is a replacement purchase

All questions regarding ownership of the products were recoded to dummy variables with value 0 for the answers of not owning the product, and value 1 for the answers indicating ownership of the product. The same procedure was followed for intention, all answers indicating that the respondent intends to buy the product were coded to value 1, and all other answers got the value 0.

Variable	**Measurement**
Knowledge base	(1) The following questions (using a 5 point Likert scale) 1. I always try to participate in the latest trends in consumer electronics. 2. I am fashionable in the area of consumer electronics. 3. I try to remain aware of the latest trends in consumer electronics. 4. I am always fast in purchasing new consumer electronics. 5. I think it is important to own new consumer electronic products. (2). The amount of consumer electronic products owned
Use of search channels	I get the idea to purchase new consumer electronics from: (using a 5 point Likert scale) 1. My own experience 2. Family living in my household 3. Friends and relatives 4. Other people around me (school or work for example) 5. People on the street 6. Through shops where I can purchase the product 7. Radio and Television 8. Advertisements and folders 9. Internet sites (no e-mail and chatting)
Intention to buy new products	The amount of products a consumer intends to buy.

Table 1: The measurement of the variables.

Further, the questionnaire enquired about the use of various search channels and the amount of influence these channels had according to the respondent when purchasing new consumer electronics.

In the previous discussion we treated the knowledge base as a homogenous concept. However there is a theoretical discussion about whether knowledge base is a homogeneous concept, or whether it has multiple dimensions (Alba and Hutchinson, 1987; Kerstetter and Cho, 2004). Because of this discussion, the knowledge base was measured in two different manners: (1) by a set of five point Likert scale questions measuring the degree to which the respondent is knowledgeable about trends in the domain of consumer electronics (used by Van Rijnsoever and Donders, 2007), and , (2) by the number of consumer electronics products that the respondent owned,. The exact operationalization is presented in Table 1.

We dealt with missing values by using multiple imputation (Donders et al., 2006) with the PRELIS program (Jöreskog and Sörbom, 2006), this resulted in 2090 usable cases (4 cases could not be imputated).

We performed an exploratory principal components analysis with a varimax rotation on the items measuring the influence of various search channels. Three factors were extracted that roughly corresponded with the three types of search channels we identified earlier (see Table 2). Component 1 corresponds to non-local search channels, component 2 to local search channels, and component 3 to own experience. These results were the basis for our model of search channels in the statistical models. For theoretical reasons we used the influence of internet sites in non-local search channels, rather than own experience, despite its higher factor loading. The factor loading can be explained by the fact that the search costs of the internet are lower than conventional channels (Bakos, 1997; Dellarocas, 2003). This made own experience a single indicator variable, for which we assumed no measurement error.

	Component		
	1	2	3
My own experience			.809
Family living in my household		.686	
Friends and relatives		.821	
Other people around me (school or work for example)		.535	
People on the street	.498		
Through shops where I can purchase the product	.698		
Radio and Television	.795		
Advertisements and folders	.763		
Internet sites (no e-mail and chatting)	.422		.641

Table 2: The results of the Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization. Values < 0.4 were suppressed for reasons of clear presentation.

For both indicators of knowledge base we fitted a structural equation model using the LISREL 8.80 program (Jöreskog and Sörbom (2006)). In estimating the structural equation model using maximum likelihood estimation, the covariance matrix turned out to be not positive definite; therefore we used Unweighted Least Squares Estimation, which is in this case the preferred alternative (Saris and Stronkhorst, 1984). The model we tested is given in Figure 3.

From the Likert-scale questions measuring knowledge base the LISREL program extracted a latent variable that represents the knowledge base. The squared variable of the knowledge base (which is an interaction of the variable with itself) was obtained by following a two-step technique (Ping, 1996) implemented in an EXCEL template (Ping, 2003). By averaging the measurement loadings of the indicators and the error terms, the EXCEL template allowed for the calculation of a factor loading and measurement error for a single indicator variable that is the squared term of the original latent linear predictor. For the use of search channels we use the same indicators as in the previous model. A latent variable was extracted from the dummy variables that represent intention to adopt new innovation. We allowed for error-covariances among the dummy variables if the modification indicated that those were necessary.

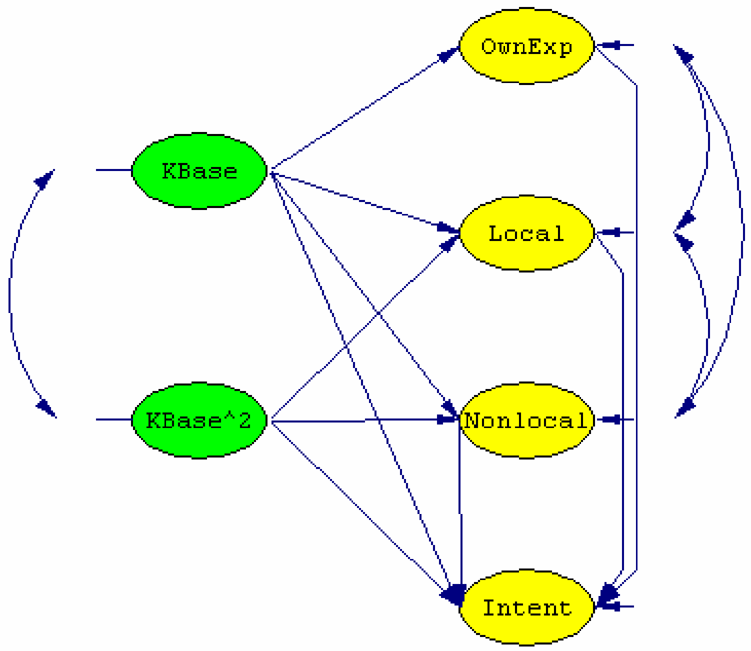

Figure 3: The structural model estimated in LISREL: KBase = Knowledge Base, KBase^2 = Knowledge Base Squared, Ownexp = Own Experience, Local = Use of Local Channels, Nonlocal = Use of Non-local Channels, Intent = Intention to adopt new innovations. The one headed arrows represent the relations that are tested, the two headed arrows represent error-covariances for the latent variables. For reasons of space the measurement model is not shown here.

Because the ownership of certain products is dependent on the ownership of other products (Rijnsoever and Castaldi, 2007), the correlation between the two indicators varies and this causes difficulties if one wants to include an interaction term as well. Further the large error-covariance between the dummies predicting the intention to adopt a certain innovation and the ownership of those innovations makes it more problematic to calculate an interaction term in a structural equation model setting that describes the quadratic effect of knowledge base. Therefore the ownership indicator of the knowledge base was a single indicator variable. The dummy variables for ownership were summed together to form the knowledge base variable. This variable was multiplied with itself to obtain the squared term. The same was done for the products the respondent intended to adopt, to form a single indicator for intention to adopt new innovations.

4. Results

We start by discussing results of the analyses predicting the use of communication channels when knowledge base is measured with the Likert scale questions (see Table 3). The dependent variables are displayed horizontally, the independent ones vertically. The cells represent the standardized estimates of each path and their p-value. A hypothesis is considered to be confirmed by the model if the sign of the estimate is in the expected direction and the p-value is smaller than 0.05. For each dependent variable, we also report the R-square value as measure for explained variance. The model, despite being a large one, has an excellent Goodness of Fit Index: 0.97. The Root Mean Square Error of Approximation (RMSEA) is 0.067 which can be considered as a good fit. The measurement matrices for this model can be found in the appendix[2].

The model convincingly shows that there is a significant relationship between the size of the knowledge base and the use of information channels. It predicts a linear relationship between the knowledge base and the use of own experience, confirming hypothesis 1; further it predicts an inverted U-shape between knowledge base and local-channels (the R-squared is relatively low though), which is in line with hypothesis 2. Also the inverted U-shape as predicted in hypothesis 3 is present. The turning point for non-local channels is further to the right than for local channels, which indicates higher search costs. The model also confirms the inverted U-shape between the knowledge base and the intention to adopt new innovations.

[2] The covariance matrix among all variables included in the model is also available from the authors upon request.

	Own experience	Local Search Channels	Non-local Search Channels	Intention to adopt new innovations
Knowledge Base	0.38***	0.13***	0.80***	0.39***
Knowledge Base^2		-0.15***	-0.16***	-0.24***
Own experience				-0.05***
Local Search Channels				-0.01
Non-local Search Channels				0.21***
R^2	0.14	0.03	0.60	0.30

Table 3: The results of the model using the Likert scale questions as measure for knowledge base.
*: p < 0.05; **: p < 0.01; ***: p <0.001. The GFI is 0.97, the RMSEA is 0.067.

The model rejects hypotheses 5 and 6. There is a very small but significant negative relationship between the use of own experience and the intention to adopt new innovations. There is no relationship between the use of local channels and the intention to adopt new innovations. However, the relationship between the use of non-local channels and the intention to adopt (hypothesis 7) is confirmed. We also estimated the mediating effect of the use of search channels on the relationship between knowledge base and intention to adopt. This indirect effect of knowledge base through the search channels is also significant (knowledge base on intention: 0.15, p<0.001; knowledge base squared: -0.03, p<0.001, not shown in the table), which proves the mediating effects of hypothesis 8.

Table 4 presents the results of the model using the single ownership indicator for knowledge base and the intention variables. The Goodness of Fit Index of the model is 0.97, again an excellent fit. The Root Mean Square Error of Approximation (RMSEA) is 0.075 which can be considered as a fine fit. For this model the measurement matrix can be found in the appendix.

	Own experience	Local Search Channels	Non-local Search Channels	Intention to adopt new innovations
Knowledge Base	0.29***	0.30***	0.70***	0.79***
Knowledge Base^2		-0.29***	-0.32***	-0.74***
Own experience				0.07***
Local Search Channels				0.06**
Non-local Search Channels				0.06***
R^2	0.08	0.01	0.17	0.07

Table 4: The results of the model using technology ownership as measure for knowledge base.
*: p < 0.05; **: p < 0.01; ***: p <0.001. The GFI is 0.97, the RMSEA is 0.075

This model also confirms hypothesis 1-3, although the R-square values are relatively low for hypothesis 1 and 2. This is due to the fact that we do not take into account measurement errors, because of the single indicator construct. The knowledge base is indeed related to the intention to adopt new innovations through an inverted U-shape, confirming hypothesis 4. The use of search channels is positively related to the intention to adopt new innovation, which confirms hypotheses 5, 6 and 7. The indirect effect of knowledge base through the search channels is again significant (knowledge base on intention: 0.08, $p<0.001$; knowledge base squared: -0.04, $p<0.001$, not shown in the table), which confirms the mediating effect predicted in hypothesis 8.

If we compare the models with the two different indicators for knowledge base, we see that there are many similarities between them. This enhances the validity of our results.

With both measurement methods, hypotheses 1, 2, 3, 4, 7 and 8 are confirmed; we therefore consider these as accepted. Hypothesis 5 was confirmed in the first model, while the second model revealed a small but significant negative relationship. In both these structural equation models however, we assumed no measurement error for this single indicator variable, an assumption that is probably not entirely true; we are therefore cautious in interpreting these results. Given the relative small effect and the assumption, it is probably safe to neglect the negative relationship produced by the first model. We then consider hypothesis 5 rejected. The first model rejects hypothesis 6, while the second model confirms this. Since the two models do not agree with each other, we consider hypothesis 6 as rejected for the moment.

5. Concluding remarks

The theoretical model proposed in this paper offers a knowledge-based perspective on the choice between different search channels that actors use to inform their adoption decisions. The basic argument that we used is that actors will attempt to minimize their search efforts; they will therefore prefer to first use their own experience (their knowledge base) to evaluate a new innovation. If their own experience is insufficient, they will resort to the next best thing, local search channels. Local channels can provide the required information relatively easily. Non-local communication channels involve the highest search costs to get the needed information.

Our model adds to the understanding of the processes underlying the diffusion of innovations. Rogers (2003) clearly states that diffusion is “the process by which (1) an *innovation* (2) is *communicated* through certain channels (3) *over time* (4) among the members of a *social system*" (p.11). Rogers stresses the importance of understanding how actors seek and process information to reduce the intrinsic uncertainty underlying the decision about the innovation. Our model makes specific claims about the relationship between the knowledge base and the search channels used for information seeking by actors confronted with the decision to innovate or not. We provide evidence showing that the use of all three channels grows as the knowledge base increases in size. Actors with a small knowledge base have insufficient knowledge to evaluate new innovations on the basis of their own experience. Therefore they turn to local search channels. At a certain critical point the actors' knowledge base has grown so large that the local information channels do not provide enough useful new information anymore. The use of local channels declines, but the importance of non-local channels and own experience continues to grow.

There comes a time when even non-local search channels do not provide sufficient information compared to the effort put into the search. In this case actors are at the 'edge of technology', in which they can only trust their own experience. The proposed relationships, depicted in Figure 2, are all confirmed in our empirical tests (hypotheses 1-3). Although the horizontal axis of the graph goes to infinity there is likely to be a point at which the cognitive capacities will start to play a limiting role on the size of the knowledge base.

We also find that having a larger knowledge base leads to a higher intention to adopt innovations (hypothesis 4). This provides a driving mechanism for the information seeking process (hypotheses 1-3). The relationship between the knowledge base and the intention to buy new products is also found to be mediated by the use of search channels. The different channels thus provide a potential feedback mechanism. If the behavioral intentions are indeed put into action, actors will increase their knowledge base up to the point when they are unable to absorb any more knowledge. Our analysis suggests that intentions are positively influenced by the accumulation of knowledge, which also explains the effect of own experience. The accumulated prior knowledge increases both positive attitudes and the perceived behavioral control of actors. The use of local search channels does not influence directly the intention to buy new products. This could mean that in the case of consumer electronics local-communication (like family or peers) channels are not decisive in establishing a subjective norm that can influence the intention to buy new products. In this case a subjective norm is shaped by non-local search channels like the internet, and mass media. We do not believe that this is a general finding, but rather a domain specific one. Further tests of our model will provide more evidence on the validity of these findings.

A direct practical implication of our results for marketing practitioners is that when advertisers send information through the non-local channels they should tailor their campaigns to the size of the knowledge base of the target consumers. If they want to target the low-knowledge audience directly they should lower the search-costs for required reliable information significantly below the level of local search costs. This will trigger a switch to those communication channels; the internet can provide an important contribution here.

The integration of organization level innovation theories (knowledge based view, evolutionary economics) with consumer learning theories has given us valuable new insights on the relationship between the existing knowledge base and the information seeking process of actors in conditions of uncertainty. Within the innovation literature and in particular the evolutionary economics strand, few attempts have been made so far to develop a theory of the demand for innovation (see Aversi et al, 1999, Cowan et al 1997 and Witt 2001 for some notable exceptions). Our theoretical exercise suggests ample room for combining insights at the intersection of organizational, marketing and economic literature.

The basic arguments that we used to build our model may easily apply to different actors and different contexts other than consumers in a product domain. Indeed the model proposed here need not be restricted to consumer behavior, but may instead be applied to the use of search channels in general. In this respect, we wish to conclude by suggesting a number of further research avenues.

First, our theory predicts that actors with a small knowledge base will be inclined to seek new information through local search channels. The switch from a local channel to a non-local channel is determined by the size of the knowledge base and the costs of finding the required information. In future research it will be important to find out what exactly determines the search costs in the specific situation. We also recommend in future studies to assess the internet as a search channel in its own right, because the search costs associated with the internet are lower than conventional media channels (Bakos, 1997; Dellacoras, 2003).

Next, to further validate the results, our tests could be replicated for other product domains or in other settings. A recent related study was conducted by Kerstetter and Cho (2004) who very specifically related past experience to the use of various search channels in the domain of tourism search behavior. However, they do not include any non-linear effects in their statistical models.

Third, we suggest that our model can be applied to other types of actors. Van Rijnsoever et al (2007) exploit similar theoretical arguments to understand the collaboration patterns among university researchers. Another avenue of research could be the application of our model to the information seeking processes of firms, and, in particular, managers. Previous research (Daft et al, 1988; McDonald and Westphal, 2003) has suggested that in conditions of higher uncertainty chief executives make more use of personal sources of information. Still, there is no formal test of the influence of prior knowledge on information seeking in this case.

Finally, so far we have looked at a model that only considers the demand side of information. Taking into account the supply side of information (e.g. opinion leaders) might also complement our understanding of information seeking processes and how they shape the demand for innovation.

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e-companion: Appendix: The measurement models of the Y-variables and the X-variables.

Search channels	(Lambda-Y)	Error variance-covariance (Theta Epsilon)								
Indicator	Estimate	1	2	3	4	5	6	7	8	9
1	1.00									
2	1.00		1.73**							
3	1.02**			1.40**						
4	1.03**		-0.64**	-0.51**	-0.57**					
5	1.00					0.78**				
6	1.20**					0.17**	1.74**			
7	1.02**					0.17**	0.45**	1.19**		
8	0.39**							0.02**	0.17**	
9	1.98**									1.13**

Table A.1: The measurement model and error variance covariance table for search channels for the first model. *: $p < 0.05$; **: $p < 0.01$. Indicator 1 is a single indicator variable for own experience with no measurement error assumed, indicators 2 and 5 are reference indicators for local and non-local search channels.

Intention	(Lambda-Y)	Error variance-covariance (Theta Epsilon)							
Indicator	Estimate	1	2	3	4	5	6	7	8
1	2.02**	0.67**							
2	1.93**		0.70**						
3	1.55**			0.80**					
4	1.69**		0.43**		0.77**				
5	1.69**					0.77**			
6	1.83**						0.73**		
7	0.62**						0.13**	0.97**	
8	1.45**					-0.16**		0.15**	0.83**
9	1.54**		0.21**		0.17**				
10	1.00							0.21**	
11	0.48**							0.27**	
12	0.09**					0.16**	0.18**	0.14**	
13	0.57**				-0.08**		0.16**	0.19**	
14	-1.12**		0.20**		0.23**		0.21**		0.17**
15	-1.54**	0.24**	0.21**	-0.58**	-0.03	0.23**	0.45**	0.11**	0.18**

Intention (continued): Error variance-covariance (Theta Epsilon)							
Indicator	9	10	11	12	13	14	15
1							
2							
3							
4							
5							
6							
7							
8							
9	0.83**						
10		0.92**					
11		0.21**	0.98**				
12		0.24**	0.23**	1.00**			
13			0.17**	0.40**	0.97**		
14	0.36**		0.31**	0.29**	0.34**	0.90**	
15	0.30**	0.43**	0.27**	0.43**	0.43**	0.28**	0.81**

Table A.2: The measurement model and error variance covariance table for the intention to adopt new innovations for the first model. *: $p < 0.05$; **: $p < 0.01$. Indicator 10 is the reference indicator.

Knowledge base	(Lambda-Y)	Error variance-covariance (Theta Epsilon)					
Indicator	Estimate	1	2	3	4	5	6
1	1.00	0.51**					
2	1.10**		0.64**				
3	1.08**			0.65**			
4	0.88**				0.43**		
5	0.87**					0.49**	
6	0.90						0.41

Table A.3: The measurement model and error variance covariance table for knowledge base for the first model. *: $p < 0.05$; **: $p < 0.01$. Indicator 1 is the reference indicator for knowledge base. Indicator 6 is the single indicator for the quadratic of knowledge base, with 0.41 error variance.

Search channels	(Lambda-Y)	Error variance-covariance (Theta Epsilon)								
Indicator	Estimate	1	2	3	4	5	6	7	8	9
1	1.00									
2	1.00		1.26**							
3	0.65**			1.67**						
4	0.35**/0.15**		-0.30**		0.06*					
5	1.00					0.38**				
6	0.74**						1.77**			
7	0.66**						0.46**	1.18**		
8	0.16**						0.20***	0.24**	0.20**	
9	2.41**					-1.16**	-0.57***	-0.52**		-1.68**

Table A.4: The measurement model and error variance covariance table for search channels for the second model. *: $p < 0.05$; **: $p < 0.01$. Indicator 1 is a single indicator variable for own experience with no measurement error assumed, indicators 2 and 5 are reference indicators for local and non-local search channels. Indicator 4 is theoretically somewhat ambiguous; it loads on both the local (0.35) and non-local search channels (0.15).